



Artificial Intelligence and Economic Growth

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in Agrawal et al *The Economics of Artificial Intelligence*, 2019

What are the implications of A.I. for economic growth?

- Build some growth models with A.I.
 - A.I. helps to make goods
 - A.I. helps to make ideas
- Implications
 - Long-run growth
 - Share of GDP paid to labor vs capital
 - Firms and organizations
- Singularity?

Two Main Themes

- A.I. modeled as a continuation of automation
 - Automation = replace labor in particular tasks with machines and algorithms
 - *Past*: textile looms, steam engines, electric power, computers
 - *Future*: driverless cars, paralegals, pathologists, maybe researchers, maybe everyone?
- A.I. may be limited by Baumol's cost disease
 - *Baumol*: growth constrained not by what we do well but rather by what is essential and yet hard to improve

Outline

- Basic model: automating tasks in production
- A.I. and the production of new ideas
- Singularity?
- Some facts



The Zeira 1998 Model

Simple Model of Automation (Zeira 1998)

- Production uses n tasks/goods:

$$Y = AX_1^{\alpha_1} X_2^{\alpha_2} \cdot \dots \cdot X_n^{\alpha_n},$$

where $\sum_{i=1}^n \alpha_i = 1$ and

$$X_{it} = \begin{cases} L_{it} & \text{if not automated} \\ K_{it} & \text{if automated} \end{cases}$$

- Substituting gives

$$Y_t = A_t K_t^\alpha L_t^{1-\alpha}$$

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- Comments:
 - α reflects the *fraction of tasks that are automated*
 - Embed in neoclassical growth model \Rightarrow

$$g_y = \frac{g_A}{1-\alpha} \quad \text{where} \quad y_t \equiv Y_t/L_t$$

- Automation: $\uparrow \alpha$ raises both capital share and LR growth
 - Hard to reconcile with 20th century
 - Substantial automation but stable growth and capital shares

Subsequent Work

- Acemoglu and Restrepo (2017, 2018, 2019, 2020, 2021, ...)
 - Old tasks are gradually automated as new (labor) tasks are created
 - Fraction automated can then be steady
 - Rich framework, with endogenous innovation and automation, all cases worked out in great detail
- Peretto and Seater (2013), Hemous and Olson (2016), Agrawal, McHale, and Oettl (2017)



Automation and Baumol's Cost Disease

Baumol's Cost Disease and the Kaldor Facts

- Baumol: Agriculture and manufacturing have rapid growth and declining shares of GDP
 - ... but also rising automation
- Aggregate capital share could reflect a **balance**
 - Rises within agriculture and manufacturing
 - But falls as these sectors decline
- Maybe this is a general feature of the economy!
 - First agriculture, then manufacturing, then services

AJJ Economic Environment

Final good $Y_t = \left(\int_0^1 X_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$ where $\sigma < 1$

Tasks $X_{it} = \begin{cases} K_{it} & \text{if automated } i \in [0, \beta_t] \\ L_{it} & \text{if not automated } i \in [\beta_t, 1] \end{cases}$

Capital accumulation $\dot{K}_t = I_t - \delta K_t$

Resource constraint (K) $\int_0^1 K_{it} di = K_t$

Resource constraint (L) $\int_0^1 L_{it} di = L$

Resource constraint (Y) $Y_t = Cons_t + I_t$

Allocation $I_t = \bar{s}_K Y_t$

Automation and growth

- Combining equations

$$Y_t = \left[\beta_t \left(\frac{K_t}{\beta_t} \right)^{\frac{\sigma-1}{\sigma}} + (1 - \beta_t) \left(\frac{L}{1 - \beta_t} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

- How β interacts with K : two effects
 - β : what fraction of tasks have been automated
 - β : Dilution as $K/\beta \Rightarrow K$ spread over more tasks
- Same for labor: $L/(1 - \beta_t)$ means given L concentrated on fewer tasks, raising “effective labor”

Rewriting in classic CES form

- Collecting the β terms into factor-augmenting form:

$$Y_t = F(B_t K_t, C_t L_t)$$

where

$$B_t = \left(\frac{1}{\beta_t} \right)^{\frac{1}{1-\sigma}} \quad \text{and} \quad C_t = \left(\frac{1}{1-\beta_t} \right)^{\frac{1}{1-\sigma}}$$

- Effect of automation: $\uparrow \beta_t \Rightarrow \downarrow B_t$ and $\uparrow C_t$

Intuition: dilution effects just get magnified since $\sigma < 1$

Automation

- Suppose a constant fraction of non-automated tasks get automated every period:

$$\dot{\beta}_t = \theta(1 - \beta_t)$$

$$\Rightarrow \beta_t \rightarrow 1$$

- What happens to $1 - \beta_t =: m_t$?

$$\frac{\dot{m}_t}{m_t} = -\theta$$

The fraction of labor-tasks falls at a constant exponential rate

Putting it all together

$$Y_t = F(B_t K_t, C_t L_t) \quad \text{where} \quad B_t = \left(\frac{1}{\beta_t} \right)^{\frac{1}{1-\sigma}} \quad \text{and} \quad C_t = \left(\frac{1}{1-\beta_t} \right)^{\frac{1}{1-\sigma}}$$

- $\beta_t \rightarrow 1 \Rightarrow B_t \rightarrow 1$
- But C_t grows at a constant exponential rate!

$$\frac{\dot{C}_t}{C_t} = -\frac{1}{1-\sigma} \frac{\dot{m}_t}{m_t} = \frac{\theta}{1-\sigma}$$

- When a constant fraction of remaining goods get automated and $\sigma < 1$, the automation model features an asymptotic BGP that satisfies Uzawa

Factor Shares of Income

- Ratio of capital share to labor share:

$$\frac{\alpha_{K_t}}{\alpha_{L_t}} = \left(\frac{\beta_t}{1 - \beta_t} \right)^{1/\sigma} \left(\frac{K_t}{L_t} \right)^{\frac{\sigma-1}{\sigma}}$$

- Two offsetting effects ($\sigma < 1$):
 - $\uparrow \beta_t$ raises the capital share
 - $\uparrow K_t/L_t$ lowers the capital share

These balance and deliver constant factor shares in the limit

$$\alpha_{K_t} \equiv \frac{F_K K}{Y} = \beta_t^{\frac{1}{\sigma}} \left(\frac{K_t}{Y_t} \right)^{\frac{\sigma-1}{\sigma}} \rightarrow \left(\frac{\bar{s}_K}{g_Y + \delta} \right)^{\frac{\sigma-1}{\sigma}} < 1$$

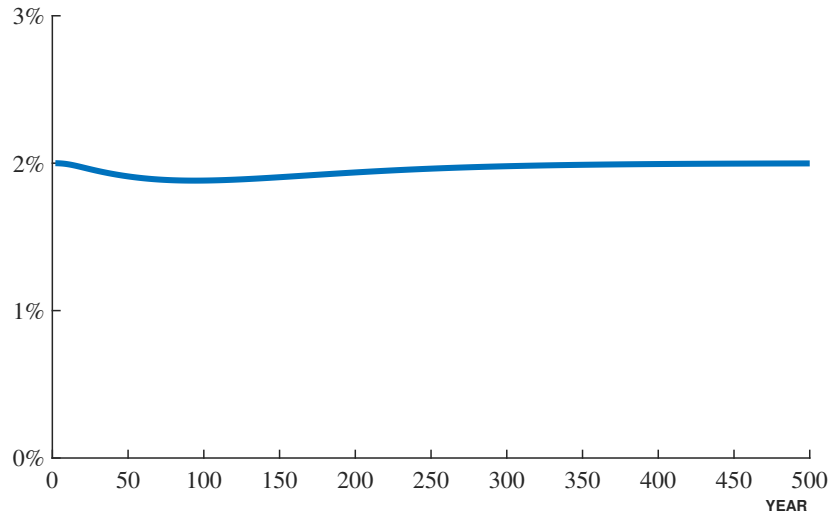
Intuition for AJJ result

- Why does automation lead to balanced growth and satisfy Uzawa?
 - $\beta_t \rightarrow 1$ so the KATC piece “ends” eventually (all tasks automated)
 - Labor per task: $L/(1 - \beta_t)$ rises exponentially over time!
 - Constant population, but concentrated on an exponentially shrinking set of goods
 \Rightarrow exponential growth in “effective” labor
- Baumol logic
 - Agr/Mfg shrink as a share of the economy...
 - Labor still gets 2/3 of GDP! Vanishing share of tasks, but all else is cheap (Baumol)

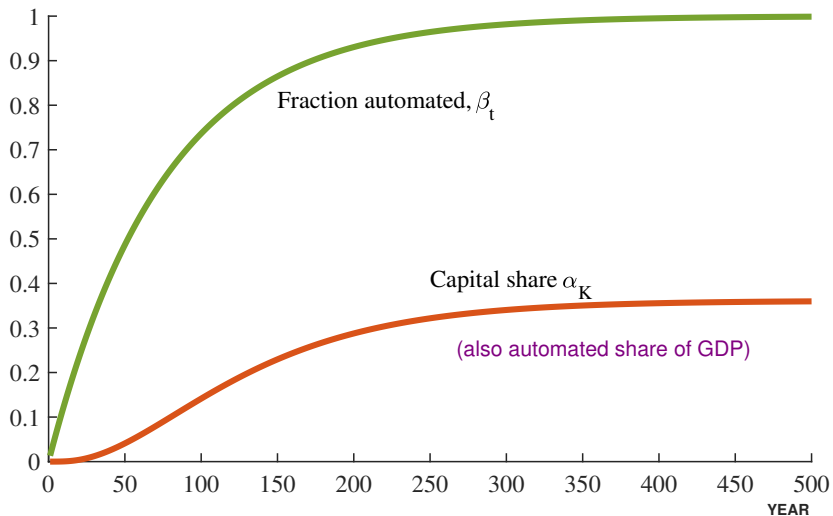
*Interesting question: What fraction of tasks automated today? β_{2022}
(B. Jones and X. Liu 2022 on capital-embodied technical change)*

Simulation: Automation and Asymptotic Balanced Growth

GROWTH RATE OF GDP



Simulation: Capital Share and Automation Fraction



Constant Factor Shares?

- Consider $g_A > 0$ — technical change beyond just automation
- Alternatively, factor shares can be constant if automation follows

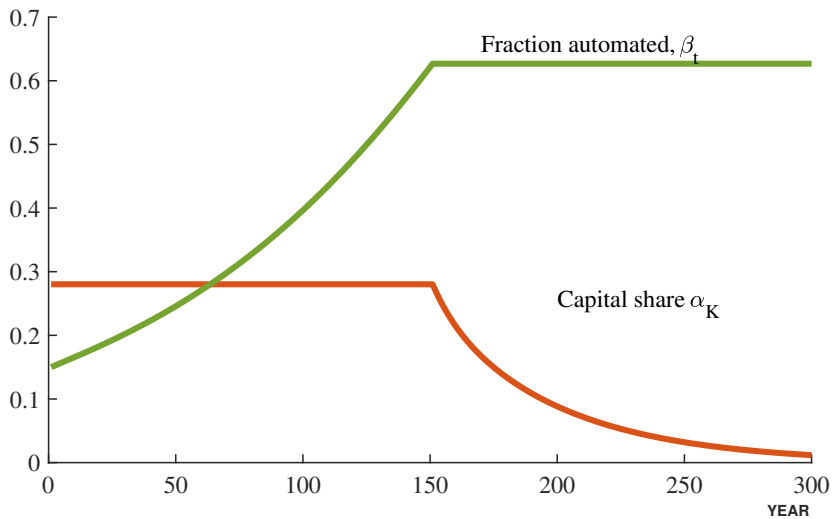
$$g_{\beta t} = (1 - \beta_t) \left(\frac{-\rho}{1 - \rho} \right) g_{kt},$$

- Knife-edge condition...
- Surprise: growth rates increase not decrease. Why? Requires

$$g_{Yt} = g_A + \beta_t g_{Kt}.$$

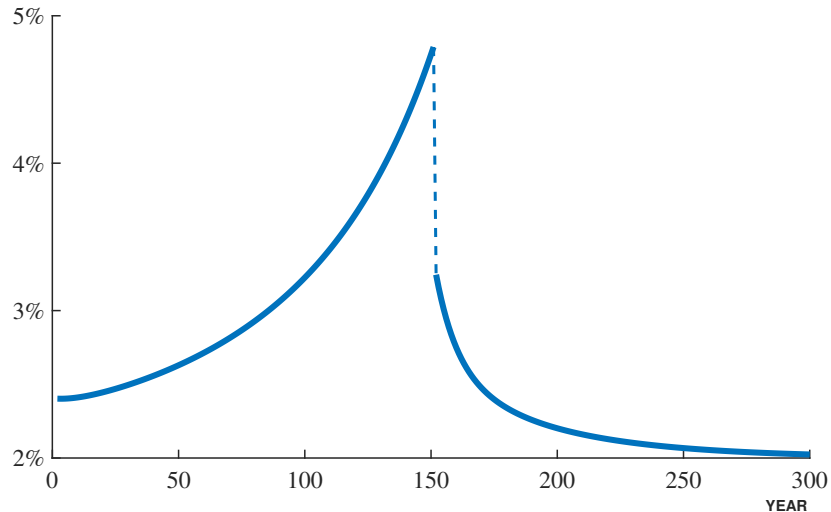
- $g_A = 0$ means zero growth. $g_A > 0$ means growth rises

Simulation: Constant Capital Share



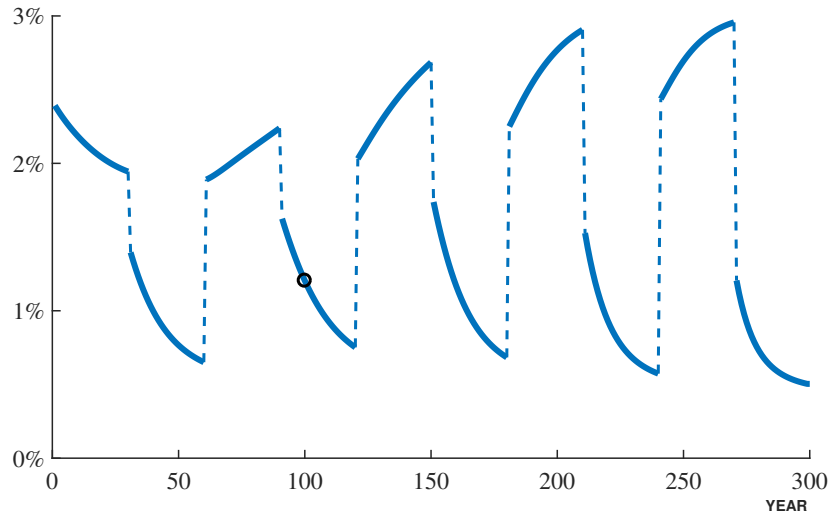
Simulation: Constant Capital Share

GROWTH RATE OF GDP

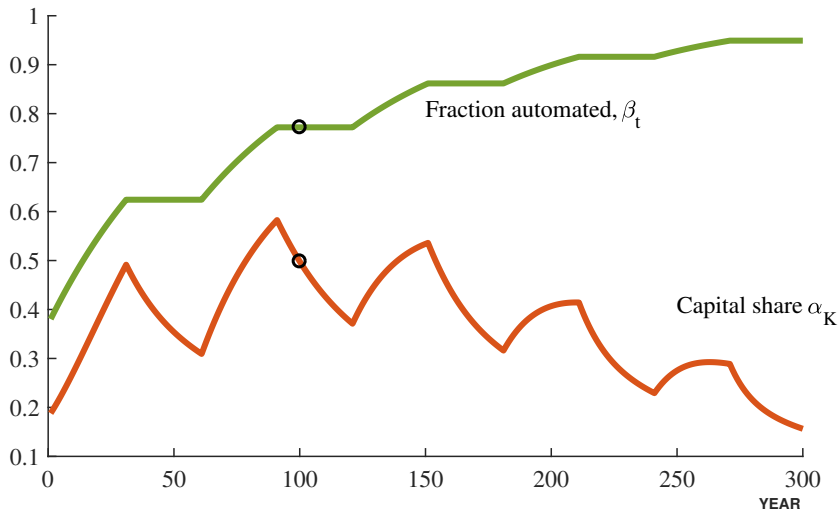


Simulation: Switching regimes...

GROWTH RATE OF GDP



Simulation: Switching regimes...





A.I. and Ideas

AI in the Ideas Production Function

- Let production of goods and services be $Y_t = A_t L_t$
- Let idea production be:

$$\dot{A}_t = A_t^\phi \left(\int_0^1 X_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma < 1$$

- Assume fraction β_t of tasks are automated by date t . Then:

$$\dot{A}_t = A_t^\phi F(B_t K_t, C_t S_t)$$

where

$$B_t = \left(\frac{1}{\beta_t} \right)^{\frac{1}{1-\sigma}} \quad \text{and} \quad C_t = \left(\frac{1}{1-\beta_t} \right)^{\frac{1}{1-\sigma}}$$

- This is like before...

AI in the Ideas Production Function

- Intuition: with $\sigma < 1$ the scarce factor comes to dominate

$$F(B_t K_t, C_t S_t) = C_t S_t F\left(\frac{B_t K_t}{C_t S_t}, 1\right) \rightarrow C_t S_t$$

- So, with continuous automation

$$\dot{A}_t \rightarrow A_t^\phi C_t S_t$$

- And asymptotic balanced growth path becomes

$$g_A = \frac{g_C + g_S}{1 - \phi}$$

- We get a “boost” from continued automation (g_C)

Can automation replace population growth?

- Maybe! Suppose S is constant, $g_S = 0$
 - Intuition: Fixed S is spread among exponentially-declining measure of tasks
 - So researchers per task is growing exponentially!
- However
 - This setup takes automation as exogenous and at “just the right rate”
 - What if automation is endogenized?
 - Is population growth required to drive automation?
 - Could a smart/growing AI entirely replace humans?



Singularities

Singularities

- Now we become more radical and consider what happens when we go “all the way” and allow AI to take over all tasks.
- **Example 1:** Complete automation of goods and services production.

$$Y_t = A_t K_t$$

→ Then growth rate can accelerate exponentially

$$g_Y = g_A + sA_t - \delta$$

we call this a “Type I” growth explosion

Singularities: Example 2

- Complete automation in ideas production function

$$\dot{A}_t = K_t A_t^\phi$$

- Intuitively, this idea production function acts like

$$\dot{A}_t = A_t^{1+\phi}$$

- Solution:

$$A_t = \left(\frac{1}{A_0^{-\phi} - \phi t} \right)^{1/\phi}$$

- Thus we can have a true **singularity** for $\phi > 0$. A_t exceeds any finite value before date $t^* = \frac{1}{\phi A_0^\phi}$.

Singularities: Example 3 – Incomplete Automation

- Cobb-Douglas, α and β are fraction automated, S constant

$$\dot{K}_t = \bar{s}L^{1-\alpha}A_t^\sigma K_t^\alpha - \delta K_t.$$

$$\dot{A}_t = K_t^\beta S^\lambda A_t^\phi$$

- Standard endogenous growth requires $\gamma = 1$:

$$\gamma := \frac{\sigma}{1-\alpha} \cdot \frac{\beta}{1-\phi}.$$

- If $\gamma > 1$, then growth explodes!
 - Can occur without full automation
 - Example: $\alpha = \beta = \phi = 1/2$ and $\sigma > 1/2$.

Objections to singularities

① Automation limits (no $\beta_t \rightarrow 1$)

② Search limits

$$\dot{A}_t = A_t^{1+\phi} \quad \text{or even} \quad A_t \leq \bar{A}$$

but $\phi < 0$ (e.g., fishing out, burden of knowledge...)

③ Natural Laws

$$Y_t = \left(\int_0^1 (a_{it} Y_{it})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{where } \sigma < 1$$

now can have $a_{it} \rightarrow \infty$ for many tasks but no singularity

- *Baumol theme*: growth determined not by what we are good at, but by what is essential yet hard to improve



Final Thoughts

Conclusion: A.I. in the Production of Goods and Services

- Introduced Baumol's "cost disease" insight into Zeira's model of automation
 - Automation can act like labor augmenting technology (surprise!)
 - Can get balanced growth with a constant capital share well below 100%, even with nearly full automation

Conclusion: A.I. in the Ideas Production Function

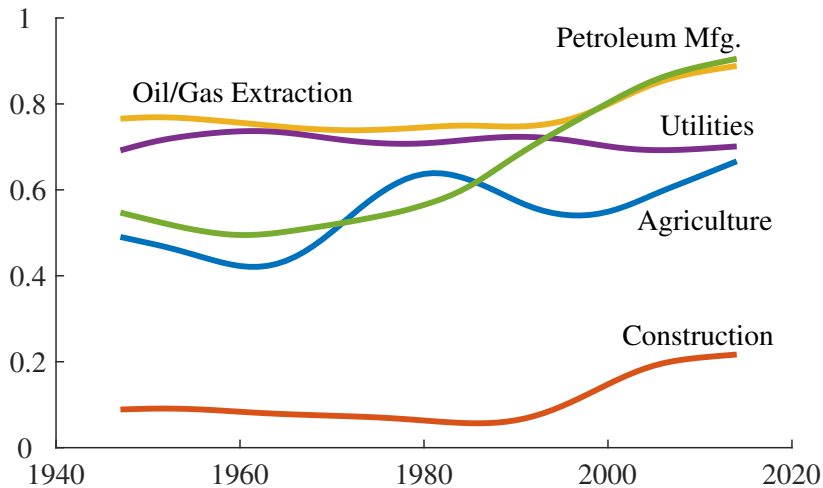
- Could A.I. obviate the role of population growth in generating exponential growth?
- Discussed possibility that A.I. could generate a singularity
 - Derived conditions under which the economy can achieve infinite income in finite time
- Discussed obstacles to such events
 - Automation limits, search limits, and/or natural laws (among others)

Extra Slides

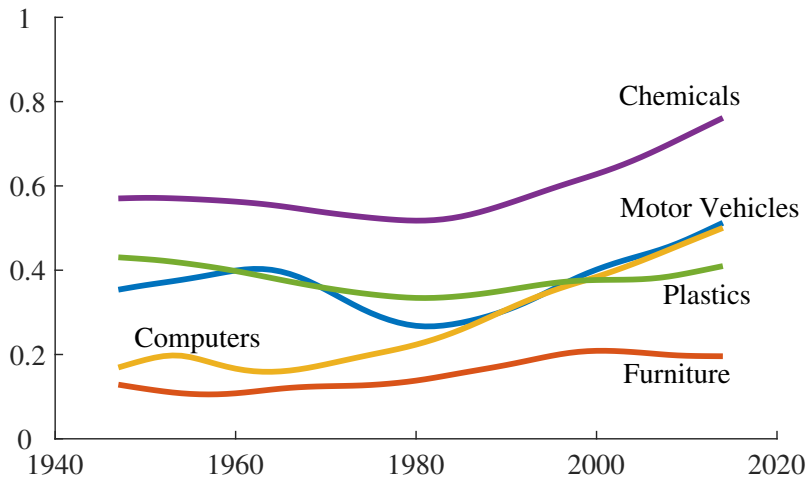


Some Facts

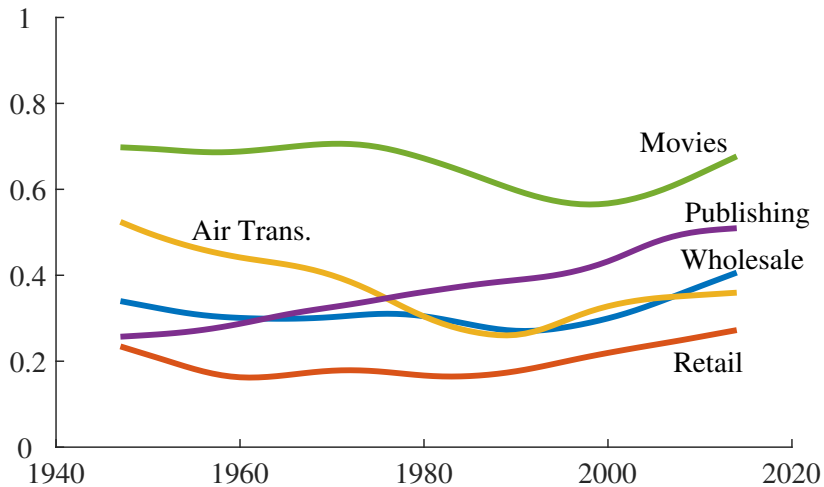
Capital Shares in U.S. Industries



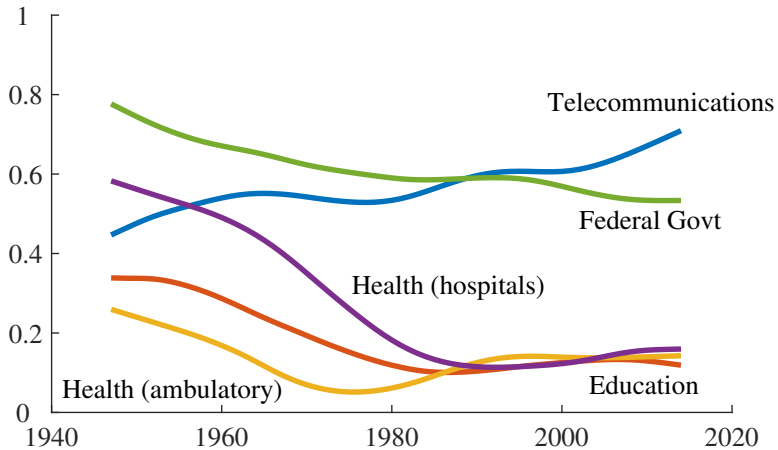
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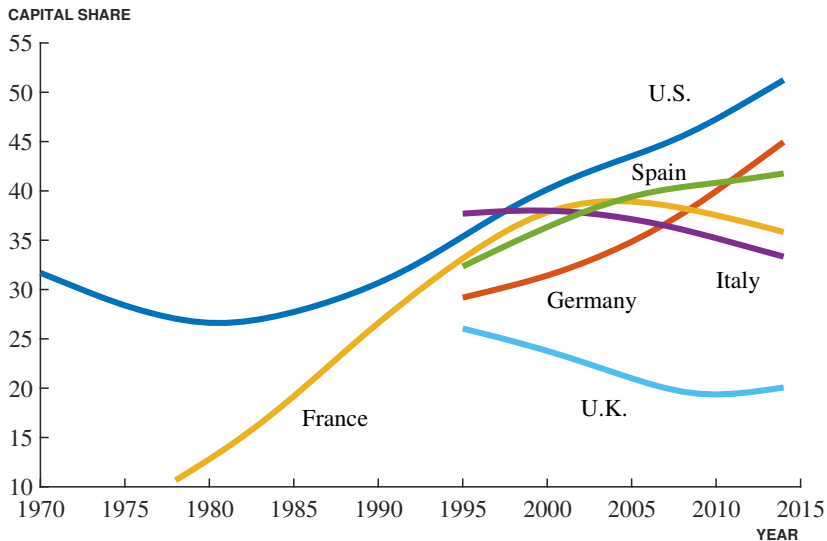
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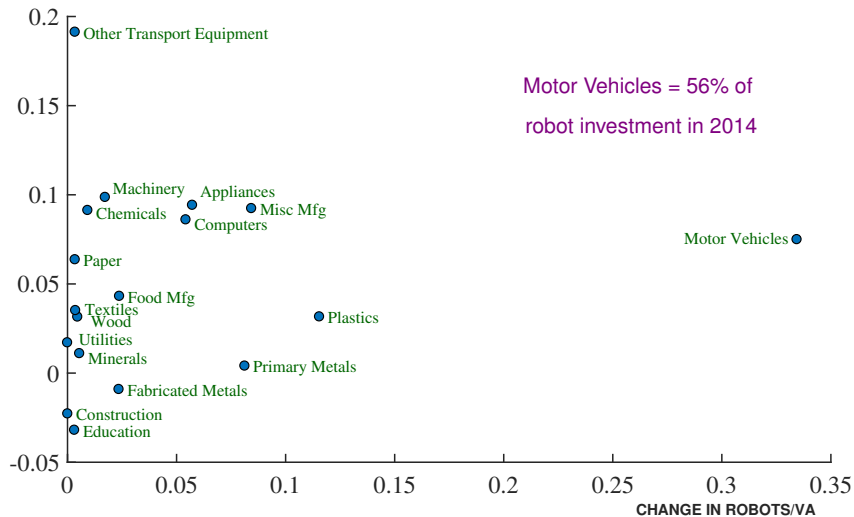


Capital Share of Income: Transportation Equipment



Adoption of Robots and Change in Capital Share

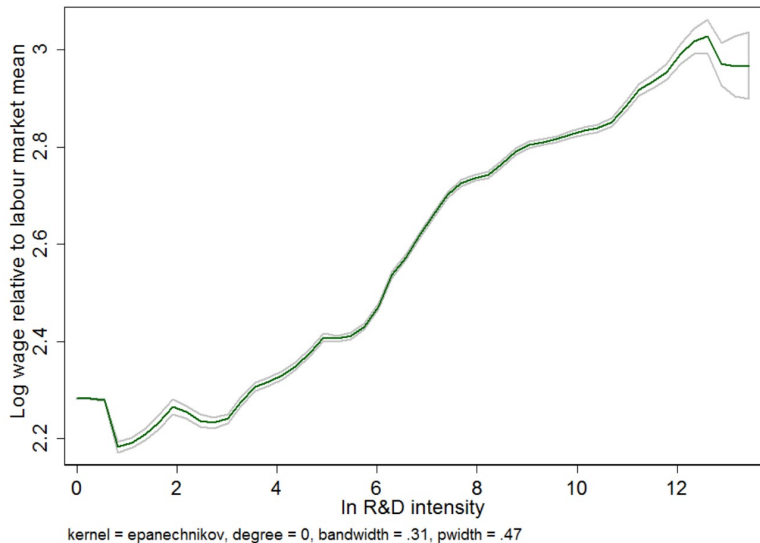
CHANGE IN CAPITAL SHARE



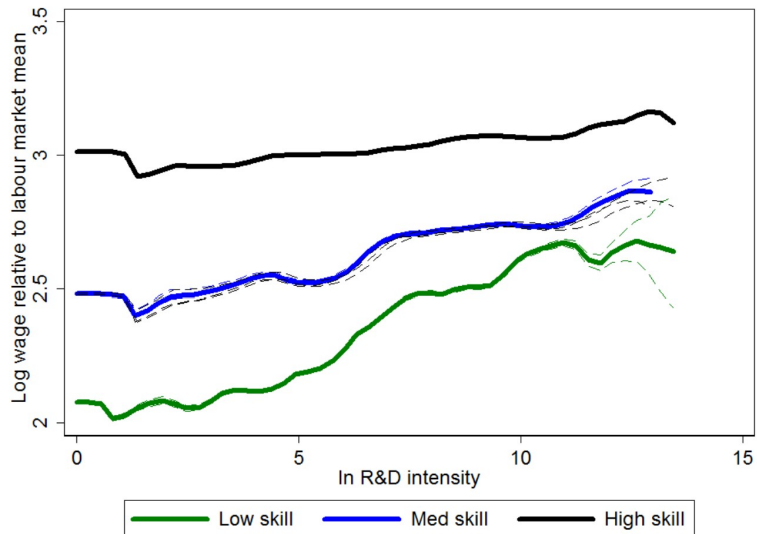
AI, Organizations, and Wage Inequality

- Usual story: robots replace low-skill labor, hence \uparrow skill premium (e.g., Krusell et al. 2000)
- But solving future problems, incl. advancing AI, might be increasingly hard, suggesting \uparrow complementarities across workers, \uparrow teamwork, and changing firm boundaries (Garicano 2000, Jones 2009)
- Aghion et al. (2017) find evidence along these lines
 - outsource higher fraction of low-skill workers
 - pay *increased* premium to low-skill workers kept

AI, Organizations, and Wage Inequality



AI, Skills, and Wage Inequality





Nonrivalry and the Economics of Data

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INET-IMF

Macroeconomics in the Age of AI

17 March 2020

Examples of Data

- Google, Facebook
- Amazon
- Tesla, Uber, Waymo
- Medical and genetic data
- Location history
- Speech records
- Physical action data

What is Data in this Paper?

- Data as a factor of production
- Data improves the quality of a product
 - We do not model data as helping a consumer or firm make a more informed decision (e.g., consumption, pricing)
- Data can be useful even if anonymous
- Other aspects of the economics of data are interesting (price discrimination, product specialization, etc.), but are purposely left out of the model

Canonical example: data as input into machine learning algorithm. E.g., medical detection algorithms, self-driving cars, voice recognition software.

Policies on Data Are Being Written Now

What policies governing data use maximize welfare?

- European General Data Protection Regulation (GDPR)
 - Privacy vs. social gain from sharing
 - “The protection of natural persons in relation to the processing of personal data is a fundamental right”
 - “The right. . . must be considered in relation to its function in society. . .”
- The California Consumer Privacy Act of 2018 (start Jan 1 2020)
 - Allows consumers to opt out of having their data sold
- US Congress: COPRA, ACCESS, etc.
- India’s Personal Data Protection bill

Data is Nonrival

- Growth literature: Ideas are nonrival
 - Unlike rival goods, ideas are **infinitely usable**
- Data is another nonrival good
 - Clearly not a blueprint / recipe \Rightarrow different from ideas
 - Ideas are production functions, data is a factor of production
 - Multiple engineers/algorithms can use same data at same time (within and across firms)
- Nonrivalry implies **increasing returns to scale**: $Y = F(D, X)$
 - Constant returns to rival inputs: $F(D, \lambda X) = \lambda F(D, X)$
 - Increasing returns to data and rival inputs:
 $F(\lambda D, \lambda X) > \lambda F(D, X)$

Data Property Rights Matter

- **Key point:** allocations with different degrees of data use
⇒ different output, welfare, etc.
- How do different property rights affect the use of data?
 - “Firms own data” versus “consumers own data”
- To illustrate, we assume (plausibly?) the Coase theorem fails
 - Consumers can't commit to selling data to just one firm
 - Firms can't commit to not using data they acquire
 - Useful for showing the role of data sharing

Data is Nonrival \Rightarrow Interesting Questions

- Do markets produce the right amount of data?
- Why don't firms (always) sell their data?
- Who should own data as it's created?
- Implications of data nonrivalry for antitrust, economic growth, and comparative advantage across countries?

We develop a framework for thinking through these questions

Outline

- Economic environment
- Allocations:
 - Optimal allocation
 - Firms own data
 - Consumers own data
 - Extreme privacy protection: outlaw data sharing
- Theory results and a numerical example



Basic Setup

Overview

- Representative consumer with a love for variety
- Innovation \Rightarrow endogenous measure of varieties
- Nonrivalry of data \Rightarrow increasing returns to scale
- How is data produced?
 - Learning by doing: each unit consumed \rightarrow 1 unit of data
 - Alternative: separate PF (Tesla vs Google self-driving car)
- Any data equally useful in all firms \Rightarrow one sector of economy
- Data depreciates fully each period

The Economic Environment

Utility	$\int_0^{\infty} e^{-\rho t} L_t u(c_t) dt$
Flow Utility	$u(c_t) = \log c_t$
Consumption per person	$c_t = \left(\int_0^{N_t} c_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$ with $\sigma > 1$
Data production	$J_{it} = c_{it} L_t$
Variety resource constraint	$c_{it} = Y_{it} / L_t$
Firm production	$Y_{it} = D_{it}^{\eta} L_{it}$, $\eta \in (0, 1)$
Data used by firm i	$D_{it} \leq \alpha x_{it} J_{it} + (1 - \alpha) B_t$ (nonrivalry)
Data of firm i used by others	$D_{sit} \leq \tilde{x}_{it} J_{it}$
Data bundle	$B_t = \left(N_t^{-\frac{1}{\epsilon}} \int_0^{N_t} D_{sit}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$ with $\epsilon > 1$
Innovation (new varieties)	$\dot{N}_t = \frac{1}{\chi} \cdot L_{et}$
Labor resource constraint	$L_{et} + \int_0^{N_t} L_{it} di = L_t$
Population growth (exogenous)	$L_t = L_0 e^{g_L t}$
Creative destruction	$\delta(\tilde{x}_{it}) = \frac{\delta_0}{2} \tilde{x}_{it}^2$ (equilibrium)

The Economic Environment: Simple Privacy Costs

Utility	$\int_0^\infty e^{-\rho t} L_t u(c_t, x_{it}, \tilde{x}_{it}) dt$
Flow Utility	$u(c_t, x_{it}, \tilde{x}_{it}) = \log c_t - \frac{\kappa}{2} \frac{1}{N_t^2} \int_0^{N_t} x_{it}^2 di - \frac{\tilde{\kappa}}{2} \frac{1}{N_t} \int_0^{N_t} \tilde{x}_{it}^2 di$
Consumption per person	$c_t = \left(\int_0^{N_t} c_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \quad \text{with } \sigma > 1$
Data production	$J_{it} = c_{it} L_t$
Variety resource constraint	$c_{it} = Y_{it} / L_t$
Firm production	$Y_{it} = D_{it}^\eta L_{it}, \quad \eta \in (0, 1)$
Data used by firm i	$D_{it} \leq \alpha x_{it} J_{it} + (1 - \alpha) B_t \quad (\text{nonrivalry})$
Data of firm i used by others	$D_{sit} \leq \tilde{x}_{it} J_{it}$
Data bundle	$B_t = \left(N_t^{-\frac{1}{\epsilon}} \int_0^{N_t} D_{sit}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} \quad \text{with } \epsilon > 1$
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Creative destruction	$\delta(\tilde{x}_{it}) = \frac{\delta_0}{2} \tilde{x}_{it}^2 \quad (\text{equilibrium})$

The Planner Problem (using symmetry of firms)

$$\max_{\{L_{pt}, x_t, \tilde{x}_t\}} \int_0^{\infty} e^{-\tilde{\rho}t} L_0 \left(\log c_t - \frac{\kappa}{2} \frac{1}{N} x_t^2 - \frac{\tilde{\kappa}}{2} \tilde{x}_t^2 \right) dt, \quad \tilde{\rho} := \rho - g_L$$

subject to

$$c_t = Y_t / L_t$$

$$Y_t = N_t^{\frac{1}{\sigma-1}} D_{it}^{\eta} L_{pt}$$

$$D_{it} = \alpha x_t Y_{it} + (1 - \alpha) N_t \tilde{x}_t Y_{it}$$

$$Y_{it} = D_{it}^{\eta} \cdot \frac{L_{pt}}{N_t}$$

$$\dot{N}_t = \frac{1}{\chi} (L_t - L_{pt})$$

$$L_t = L_0 e^{g_L t}$$

- More sharing \Rightarrow negative utility cost but more consumption
- Balance labor across production and entry/innovation

Scale Effect from Sharing Data

$$D_{it} = \alpha x_t J_{it} + (1 - \alpha) \left(N_t^{-\frac{1}{\epsilon}} \int_0^{N_t} (\tilde{x}_t J_{it})^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$$

$$\begin{aligned} D_{it} &= \alpha x_t Y_{it} + (1 - \alpha) N_t \tilde{x}_t Y_{it} \\ &= [\alpha x_t + (1 - \alpha) \tilde{x}_t N_t] Y_{it} \end{aligned}$$

- No sharing versus sharing:
 - **No sharing:** Only the αx_t term = no scale effect
 - **Sharing:** The $(1 - \alpha) \tilde{x}_t N_t$ term = extra scale effect

Source of Scale Effect: N_t scales with L_t

- Plugging into production function:

$$Y_{it} = ([\alpha x_t + (1 - \alpha) \tilde{x}_t N_t]^\eta L_{it})^{\frac{1}{1-\eta}}$$

The Optimal Allocation on BGP (asymptotic)

$$\tilde{x}_{it} = \tilde{x}_{sp} = \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \right)^{1/2} \quad (1)$$

$$x_{it} = x_{sp} = \frac{\alpha}{1-\alpha} \frac{\tilde{\kappa}}{\kappa} \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \right)^{1/2} \quad (2)$$

$$L_{it}^{sp} = \chi \rho \cdot \frac{\sigma-1}{1-\eta} := \nu_{sp} \quad (3)$$

$$N_t^{sp} = \frac{L_t}{\chi (g_L + \nu_{sp})} := \psi_{sp} L_t \quad (4)$$

$$L_{pt}^{sp} = \nu_{sp} \psi_{sp} L_t \quad (5)$$

$$Y_t^{sp} = (\nu_{sp} (1-\alpha)^\eta \tilde{x}_{sp}^\eta)^{\frac{1}{1-\eta}} (\psi_{sp} L_t)^{\frac{1}{\sigma-1} + \frac{1}{1-\eta}} \quad (6)$$

$$c_t^{sp} = \frac{Y_t}{L_t} = (\nu_{sp} (1-\alpha)^\eta \tilde{x}_{sp}^\eta)^{\frac{1}{1-\eta}} (\psi_{sp} L_t)^{\frac{1}{\sigma-1} + \frac{\eta}{1-\eta}} \quad (7)$$

$$g_c^{sp} = \left(\frac{1}{\sigma-1} + \frac{\eta}{1-\eta} \right) g_L \quad (8)$$

$$D_i^{sp} = ((1-\alpha) \tilde{x}_{sp} \nu_{sp} \psi_{sp} L_t)^{\frac{1}{1-\eta}} \quad (9)$$

$$D^{sp} = N D_i = ((1-\alpha) \tilde{x}_{sp} \nu_{sp})^{\frac{1}{1-\eta}} (\psi_{sp} L_t)^{1 + \frac{1}{1-\eta}} \quad (10)$$

$$Y_{it}^{sp} = (\nu_{sp} (1-\alpha)^\eta \tilde{x}_{sp}^\eta)^{\frac{1}{1-\eta}} (\psi_{sp} L_t)^{\frac{\eta}{1-\eta}} \quad (11)$$

The Optimal Allocation: GDP per person

$$c_t^{sp} = \frac{Y_t}{L_t} = \left(\nu_{sp} (1 - \alpha)^\eta \tilde{x}_{sp}^\eta \right)^{\frac{1}{1-\eta}} (\psi_{sp} L_t)^{\frac{1}{\sigma-1} + \frac{\eta}{1-\eta}}$$

$$g_c^{sp} = \left(\frac{1}{\sigma-1} + \frac{\eta}{1-\eta} \right) g_L$$

- Scale effect: $\underbrace{\frac{1}{\sigma-1}}_{\text{Love of Variety}} + \underbrace{\frac{\eta}{1-\eta}}_{\text{Data}}$

- More people make more data and all firms use all shared data

The Optimal Allocation: Data, Firm Size, Variety

$$\tilde{x}_{sp} = \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1 - \eta} \right)^{1/2}$$
$$L_{it}^{sp} = \chi\rho \cdot \frac{\sigma - 1}{1 - \eta} := \nu_{sp}$$
$$N_t^{sp} = \frac{L_t}{\chi g_L + \nu_{sp}} := \psi_{sp} L_t$$

- Data shared increasing in data production elasticity and decreasing in privacy cost
- Firm size constant on BGP. N has opposite comparative statics
- Higher entry cost, time preference, population growth, and elasticity of substitution raise firm size and reduce varieties
- Higher η raises firm size and reduces varieties:
Entry does not create data



Firms Own Data

Firms Own Data: Consumer Problem

- Firms own data and choose one data policy (x_{it}, \tilde{x}_{it}) applied to all consumers
- Consumers just choose consumption:

$$U_0 = \max_{\{c_{it}\}} \int_0^{\infty} e^{-\tilde{\rho}t} L_0 u(c_t, x_{it}, \tilde{x}_{it}) dt$$
$$\text{s.t. } c_t = \left(\int_0^{N_t} c_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$
$$\dot{a}_t = (r_t - g_L)a_t + w_t - \int_0^{N_t} p_{it} c_{it} di$$

Firms own Data: Data Decisions

- Firms buy D_{bit} data from intermediary at given price p_b
- Firms sell D_{sit} data to intermediary at chosen price p_{si}
 - Perfect competition inconsistent with nonrival data!
 - Monopolistically competitive with own data
 - See the intermediary's downward-sloping demand curve and set price
- How much data to use / sell?
 - x_{it} : Use all of own data $\Rightarrow x_{it} = 1$
 - \tilde{x}_{it} : Trade off = selling data versus creative destruction
 $\delta(\tilde{x}_{it})$ = Poisson rate transferring ownership of variety

Firms own the Data: Incumbent Firm Problem

- Monopolistically competitive firm takes demand for variety as given (from FOC of consumer problem): $p_{it} = \left(\frac{c_t}{c_{it}}\right)^{\frac{1}{\sigma}} = \left(\frac{Y_t}{Y_{it}}\right)^{\frac{1}{\sigma}}$

$$r_t V_{it} = \max_{L_{it}, D_{bit}, x_{it}, \tilde{x}_{it}} \left(\frac{Y_t}{Y_{it}}\right)^{\frac{1}{\sigma}} Y_{it} - w_t L_{it} - p_{bt} D_{bit} + p_{st} \tilde{x}_{it} Y_{it} + \dot{V}_{it} - \delta(\tilde{x}_{it}) V_{it}$$

s.t.

$$Y_{it} = D_{it}^{\eta} L_{it}$$
$$D_{it} = \alpha x_{it} Y_{it} + (1 - \alpha) D_{bit}$$
$$x_{it} \in [0, 1], \tilde{x}_{it} \in [0, 1]$$
$$p_{sit} = \lambda_{DI} N_t^{-\frac{1}{\epsilon}} \left(\frac{B_t}{\tilde{x}_{it} Y_{it}}\right)^{\frac{1}{\epsilon}}$$

- Data Intermediary (p_{bt}, p_{st}, D_{bit}) and Free Entry complete eqm.

Firms own the Data: Data Intermediary Problem

- A monopolist takes data purchase price as given and sees the downward sloping demand curve for data $p_{bt}(D_{bit})$:

$$\max_{p_{bt}, D_{sit}} p_{bt} \int_0^{N_t} D_{bit} di - p_{st} \int_0^{N_t} D_{sit} di$$

s.t.

$$D_{bit} \leq B_t = \left(N_t^{-\frac{1}{\epsilon}} \int_0^{N_t} D_{sit}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$$

$$p_{bt} \leq p_{bt}^*$$

- Free entry at zero cost \Rightarrow zero profits
- Problem incorporates **data nonrivalry**
 - Buys data once from each firm
 - But can sell the same bundle multiple times

Entry: Innovation Creates a New Variety

- χ units of labor needed to create an additional variety
- Free entry condition:

$$\chi w_t = V_{it} + \frac{\int_0^{N_t} \delta(\tilde{x}_{it}) V_{it} di}{\dot{N}_t}$$

- The value of a new variety and the per-entrant share of business stealing from creative destruction

Firms Own Data: A “No Trade” Law

- What if the government, in an attempt to protect consumers privacy, makes data sharing illegal?
- Government chooses
 - $x_{it} \in (0, 1]$
 - $\tilde{x}_{it} = 0$
- We call this the “Outlaw Sharing” allocation



Consumers Own Data

Consumers own Data: Consumer Problem

- Consumers own data, so now choose how much to sell (x_{it}, \tilde{x}_{it}):

$$U_0 = \max_{\{c_{it}, x_{it}, \tilde{x}_{it}\}} \int_0^{\infty} e^{-\tilde{\rho}t} L_0 u(c_t, x_{it}, \tilde{x}_{it}) dt$$
$$\text{s.t. } c_t = \left(\int_0^{N_t} c_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$
$$\dot{a}_t = (r_t - g_L) a_t + w_t - \int_0^{N_t} p_{it} c_{it} di + \int_0^{N_t} x_{it} p_{st}^a c_{it} di + \int_0^{N_t} \tilde{x}_{it} p_{st}^b c_{it} di$$

- Firm problem similar to before, but now takes x, \tilde{x} as given, can't sell data, and has to buy "own" data

Consumers own the Data: Incumbent Firm Problem

- Monopolistically competitive firm takes demand for variety as given (from FOC of consumer problem):

$$q_{it} = \left(\frac{c_t}{c_{it}}\right)^{\frac{1}{\sigma}} = \left(\frac{Y_t}{Y_{it}}\right)^{\frac{1}{\sigma}} = p_{it} - x_{it}p_{st}^a - \tilde{x}_{it}p_{st}^b$$

- Firm buys data on its own variety (D_{ait}) and data on other firms varieties (D_{bit})

$$r_t V_{it} = \max_{L_{it}, D_{ait}, D_{bit}} \left[\left(\frac{Y_t}{Y_{it}}\right)^{\frac{1}{\sigma}} + p_{st}^a x_{it} + p_{st}^b \tilde{x}_{it} \right] Y_{it} - w_t L_{it} \\ - p_{at} D_{ait} - p_{bt} D_{bit} + \dot{V}_{it} - \delta(\tilde{x}_t) V_{it}$$

$$\text{s.t. } Y_{it} = D_{it}^{\eta} L_{it}$$

$$D_{it} = \alpha D_{ait} + (1 - \alpha) D_{bit}$$

$$D_{ait} \geq 0, \quad D_{bit} \geq 0$$

Key Forces: Consumers vs. Firms vs. Outlaw Sharing

- Firms
 - use all data on own variety, ignoring consumer privacy
 - restrict data sharing because of creative destruction
- Consumers
 - respect their own privacy concerns
 - sell data broadly, ignoring creative destruction
- Outlaw sharing
 - maximizes privacy gains
 - missing scale effect reduces consumption



Results: Comparing Allocations

1. Planner Problem
2. Firms Own Data
3. Outlaw Data Sharing
4. Consumers Own Data

Key Allocations: $alloc \in \{sp, f, c, ns\}$

- Firm size: $L_i^{alloc} = L_{pt}/N_t = \nu_{alloc}$

$$\nu_{sp} := \chi\rho \cdot \frac{\sigma - 1}{1 - \eta}$$

$$\nu_{os} := \chi\rho \cdot \frac{\sigma - 1}{1 - \sigma\eta}$$

$$\nu_c := \chi g_L \cdot \frac{\rho + \delta(\tilde{x}_c)}{g_L + \delta(\tilde{x}_c)} \cdot \frac{\sigma - 1}{1 - \sigma\eta}$$

$$\nu_f := \chi g_L \cdot \frac{\rho + \delta(\tilde{x}_f)}{g_L + \delta(\tilde{x}_f)} \cdot \frac{\sigma - 1}{1 - \sigma\eta \frac{\epsilon - 1}{\epsilon}}$$

- Number of firms: $N_t^{alloc} = \psi_{alloc} L_t$

$$\psi_{alloc} := \frac{1}{\chi g_L + \nu_{alloc}}$$

Output

- For $alloc \in \{sp, c, f\}$:

$$Y_t^{alloc} = [\nu_{alloc}(1 - \alpha)^\eta \tilde{x}_{alloc}^\eta]^{1-\eta} (\psi_{alloc} L_t)^{1 + \frac{1}{\sigma-1} + \frac{\eta}{1-\eta}}$$

- For Outlaw Sharing:

$$Y_t^{os} = [\nu_{os} \alpha^\eta x_{os}^\alpha]^{1-\eta} (\psi_{os} L_t)^{1 + \frac{1}{\sigma-1}}$$

- Two source of increasing returns to scale:
 - Standard variety effect: $\frac{\sigma}{\sigma-1}$
 - Data sharing: $\frac{\eta}{1-\eta}$
- Recall $\tilde{x}_t > 0$ from data sharing \Rightarrow **scale effect**

Data Sharing

Own Firm Data

$$x_{sp} = \frac{\alpha}{1-\alpha} \frac{\tilde{\kappa}}{\kappa} \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \right)^{1/2}$$

$$x_f = 1$$

$$x_{os} \in (0, 1]$$

$$x_c = \frac{\alpha}{1-\alpha} \frac{\tilde{\kappa}}{\kappa} \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \cdot \frac{\sigma-1}{\sigma} \right)^{1/2}$$

Sharing with Other Firms

$$\tilde{x}_{sp} = \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \right)^{1/2}$$

$$\tilde{x}_f = \left(\frac{2\Gamma\rho}{(2-\Gamma)\delta_0} \right)^{1/2}, \Gamma := \frac{\eta(\sigma-1)}{\epsilon-1-\sigma\eta}$$

$$\tilde{x}_{os} = 0$$

$$\tilde{x}_c = \left(\frac{1}{\tilde{\kappa}} \cdot \frac{\eta}{1-\eta} \cdot \frac{\sigma-1}{\sigma} \right)^{1/2}$$

- Firms fear creative destruction and share less than planner (δ_0)
- Consumers share less than planner because of mark up
- No sharing law restricts data even more
- Firms use more own-variety data compared to consumer/planner

Numerical Example: Parameter Values

Description	Parameter	Value
Importance of data	η	0.06
Elasticity of substitution	σ	4
Weight on privacy	$\kappa = \tilde{\kappa}$	0.20
Population level	L_0	100
Population growth rate	g_L	0.02
Rate of time preference	ρ	0.025
Labor cost of entry	χ	0.01
Creative destruction	δ_0	0.4
Weight on own data	α	1/2
Elasticity of Substitution (data)	ϵ	50
Use of own data in NS	\bar{x}	1

Numerical Example: How large is η ? (Approach 1 - Data Share)

- Share of GDP spent on data = $\frac{\eta}{1-\eta} \frac{\sigma-1}{\sigma}$
- Similar formula/quantity when consumers or firms own data
- Set $\sigma = 4$
- If data share of GDP is 5% $\Rightarrow \eta = 0.0625$
- If data share of GDP is 10% $\Rightarrow \eta = 0.12$
- Approach will be to explore $\eta \in \{0.03, 0.06, 0.12\}$

Numerical Example: Consumption Equivalent Welfare

$$U_{ss}^{alloc} = \frac{1}{\tilde{\rho}} \left(\log c_0^{alloc} - \frac{\tilde{\kappa}}{2} \tilde{x}_{alloc}^2 + \frac{g_c^{alloc}}{\tilde{\rho}} \right).$$

Let $U_{ss}^{alloc}(\lambda)$ denote steady-state welfare when we perturb the allocation of consumption by some proportion λ :

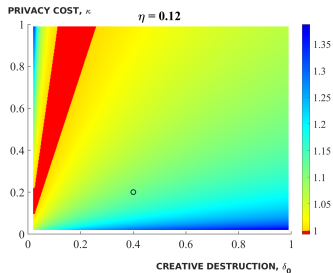
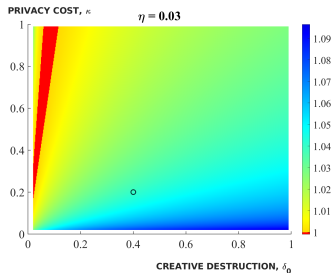
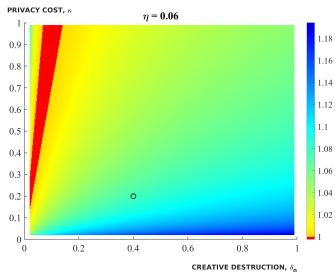
$$U_{ss}^{alloc}(\lambda) = \frac{1}{\tilde{\rho}} \left(\log(\lambda c_0^{alloc}) - \frac{\tilde{\kappa}}{2} \tilde{x}_{alloc}^2 + \frac{g_c^{alloc}}{\tilde{\rho}} \right).$$

Define consumption equivalent welfare as λ^{alloc} :

$$U_{ss}^{sp}(\lambda^{alloc}) = U_{ss}^{alloc}(1) \text{ with}$$

$$\log \lambda^{alloc} = \underbrace{\log c_0^{alloc} - \log c_0^{sp}}_{\text{Level term}} - \underbrace{\frac{\tilde{\kappa}}{2} (\tilde{x}_{alloc}^2 - \tilde{x}_{sp}^2)}_{\text{Privacy term}} + \underbrace{\frac{g_c^{alloc} - g_c^{sp}}{\tilde{\rho}}}_{\text{Growth term}}$$

Welfare Sensitivity Analysis (η, δ, κ): λ^c/λ^f



Allocations: Baseline

Allocation	Data Sharing		Firm size ν	Variety $N/L = \psi$	Consumption c	Growth g	Creative Destruct. δ
	"own" x	"others" \tilde{x}					
Social Planner	0.66	0.66	1304	665	18.6	0.67%	0.0870
Consumers Own Data	0.59	0.59	1482	594	18.3	0.67%	0.0696
Firms Own Data	1	0.16	1838	491	16.0	0.67%	0.0052
Outlaw Sharing	1	0	2000	455	7.3	0.50%	0

- Firms overuse their own data and undershare with others
- Consumers share less data than planner, but not by much
- Growth rate scale effect is modest, level differences are large

Consumption Equivalent Welfare

Allocation	Welfare λ	$\log \lambda$	Level term	Privacy term	Growth term
Optimal Allocation	1	0
Consumers Own Data	0.9886	-0.0115	-0.0202	0.0087	0.0000
Firms Own Data	0.8917	-0.1146	-0.1555	0.0409	0.0000
Outlaw Sharing	0.3429	-1.0703	-0.9399	0.0435	-0.1739

- Outlaw sharing: particularly harmful law (66 percent worse!)
- Firms own data: substantially lower welfare (11 percent worse)
- Consumers own data: nearly optimal (1 or 2 percent worse)

Implications for IO

- Firms that use data might grow fast compared to those that don't
- Firms would like to merge into one single economy-wide firm
 - Implications for antitrust
 - Price/quantity behavior
- What are the costs of forced sharing?
 - Disincentive to collect/create data
 - Data as a barrier to entry
(extension to quality ladder model)
 - Markets unraveling
- Targeted mandatory sharing?
 - E.g., airplane safety (after a crash)

Data versus Ideas: Excludability

- Maybe technologically easier to transmit data than ideas (usb key vs. education) . . .
- But data can be encrypted and monitored
- Data seems highly excludable
 - Idea: use machine learning to train self-driving car algorithm
 - ML needs lots of data. Each firm gathering own data

The Boundaries of Data Diffusion: Firms and Countries

- How does data diffuse across firms and countries?
 - Ideas eventually diffuse across firms or countries, so no country scale effect (e.g. HK vs China)
 - What about data?
- Scale effects and country size
 - Larger countries may have an important advantage as data grows in importance
- Scale effects and institutions
 - What if China mandates data sharing across Chinese firms and U.S. has no such policy
 - What if consumers in China have different privacy concerns than in the U.S. or Europe?

Conclusion

- Nonrival data \Rightarrow large social gain from sharing data
- If firms own data, they may:
 - privately use more data than consumers/planner would
 - sell less data across firms than consumers/planner would
- Nonrivalry \Rightarrow Laws that outlaw sharing could be very harmful
- Consumers owning data good at balancing privacy and sharing